J Forensic Sci, November 2008, Vol. 53, No. 6
doi: 10.1111/j.1556-4029.2008.00873.x
Available online at: www.blackwell-synergy.com

Michael G. Vaughn,[1] *Ph.D.; Matt DeLisi,*[2] *Ph.D.; Kevin M. Beaver,*[3] *Ph.D.; and Matthew O. Howard,*[4] *Ph.D.*

Toward a Quantitative Typology of Burglars: A Latent Profile Analysis of Career Offenders

ABSTRACT: Burglary is a serious, costly, and prevalent crime but prior typologies of burglars are mostly speculative and based on qualitative data. Using a sample of 456 adult career criminals, the current study used latent profile analysis to construct a methodologically rigorous quantitative typology. Four classes of burglars emerged: *young versatile*, *vagrant, drug-oriented*, and *sexual predators*. All groups demonstrated significant involvement in varied forms of crime, but the sexual predator group was the most violent and had the most serious criminal careers. Connections to the criminal career literature are offered and suggestions for further empirical study of offender typologies are discussed.

KEYWORDS: forensic science, burglary, criminal profiling, offender typology, latent profile analysis, criminal career

The substantial economic and social costs of burglary warrant increased scientific advancement in the classification and subtyping of burglars. Last year, more than 2.1 million burglaries were reported for law enforcement, accounting for 21.2% of property crimes, resulting in an average financial loss of $1,725 (1). In terms of criminal justice expenditures and collateral victimization costs, the average social cost per burglary has been estimated at nearly $20,000 (2). Most burglars are also involved with other offenses, such as robbery, assault, and drug selling (3,4). Despite being a relatively common felony, few studies have attempted to develop quantitatively based taxonomies of burglar subtypes. As a result, much information on burglars is derived from the offender's perspectives via ethnographic research and case studies.

In contrast, the criminal careers paradigm has emerged as one of the foremost paradigms in criminology. Rather than viewing criminal activity such as burglary as a solitary event from the personal perspective of a single offender, the criminal careers perspective studies antisocial behavior longitudinally, usually quantitatively, and explores the ways that criminal offending patterns emerge, continue, escalate, desist, and ultimately end. A major area of study within criminal careers research centers on the utility of categorical classifications of offenders or typologies that organize offenders according to their discrete offending patterns. Although some evidence of offense specialization has been found which would support the use of typologies, most research indicates that criminal offenders are versatile in their offending patterns (5,6). This means that burglary usually occurs along with other types of antisocial behavior; unfortunately, the understanding of how burglary relates to other types of offenses and what its place is in the criminal career is still in progress.

[1]University of Pittsburgh, School of Social Work, 2117 Cathedral of Learning, Pittsburgh, PA 15260.
[2]Department of Sociology, Iowa State University, 203A East Hall, Ames, IA 50011-1070.
[3]College of Criminology and Criminal Justice, Florida State University, 634 West Call Street, Tallahassee, FL 32306-1127.
[4]Frank A. Daniels, School of Social Work, University of North Carolina, 325 Pittsboro, Chapel Hill, NC 27599.

Received 28 July 2007; and in revised form 16 Mar. 2008; accepted 29 Mar. 2008.

Several studies of burglars from the offender's perspective have found that burglars are deliberate in choosing targets and often engage in careful planning (7–13). Findings relevant to the development of typologies of burglars have emerged from these investigations. In a study of 105 residential burglars, Decker et al. (9) found that many burglars engaged in burglaries because it was perceived as a relatively easy way to make money for lifestyle support often involving significant and expensive quantities of drugs and alcohol. Moreover, many perpetrators found the enterprise of burglary to be thrilling, a finding that is concordant with ethnographic research (3,8,14,15). According to a typology developed by Maguire and Bennett (10), three types of burglars can be identified: low-level amateurs, mid-level professionals, and high-level professional burglars. Most of them are low-level or mid-level burglars. In a forensic psychiatric study of sexually oriented burglars, Schlesinger and Revitch (16) found that sexual burglars could be usefully classified into two groups: overt sexual burglars who seek sexual gratification via direct involvement in sexual acts committed during burglaries and covert sexual burglars who are more voyeuristic. Taken together, these studies indicate a broad pattern of themes involving material gain, sexual drive, and substance abuse. Although generating useful insights, these typologies were not developed through rigorous quantitative analysis and were not situated within a criminal careers framework.

The aim of the present investigation was to take a rigorous quantitative approach to taxonomic classification of burglars. We identified burglar subtypes using latent profile analysis (LPA) of data on the criminal careers of a sample of 456 burglars. An empirically derived typology such as that developed in this study could serve to synthesize competing conceptualizations of burglar subtypes and provide an initial starting point for future investigations that attempt to subtype burglars using latent variable modeling or qualitative inductive techniques.

Methods

Sampling and Procedures

The study of active, career offenders who are burglars poses a multitude of methodological difficulties for researchers. Such persons are not easily identifiable in general population samples. For example, DeLisi (17,18) found that little was known about the offending careers of extreme habitual criminals because most criminal career datasets lacked sufficient numbers of the most serious offenders. Consequently, an offender sample must be large enough to yield enough offenders with burglary offenses to support multivariate statistical analyses. From 1995 to 2000, the second author of this report was employed as a bond commissioner at a large urban jail located in Colorado. In this particular jurisdiction, bond commissioners served as judicial officers and worked in conjunction with sheriff deputies within the county jail. Their function was to interview all criminal defendants brought to the jail and to obtain employment, residency, and criminal history data for setting bond. This work experience permitted continuous access (the bond commissioner unit was staffed 24 h a day) to all arrestees who were brought to the jail during this time period. Data pertaining to the present study sampling frame were derived from an effort to identify the most recidivistic offenders to determine their eligibility for various social services and to facilitate prosecutorial efforts. A pilot study of *c.* 50 offenders comprised the original frequent offender sample; their criminal histories contained an average of 30 arrest charges. Using this selection criterion, any offender whose record contained 30 or more arrest charges was classified as a frequent offender contingent upon the approval of the chief district judge and district attorney's office. From 1995–2000, the bond commissioner unit processed 25,640 defendants, 500 of whom (less than 2%) qualified for frequent offender status. These 500 offenders were, in effect, the frequent offender population of a 6-year census of official criminal offenders processed in this jurisdiction. Importantly, although offenders were processed at one facility, their criminal activity could and did occur in multiple jurisdictions. Of the 500 frequent offenders identified, the final study sample comprised of 456 adults who possessed a history of burglary offenses. Sample characteristics are presented in Table 1.

Data and Measures

During bond interviews (which were legal proceedings conducted under oath), defendants self-reported their criminal history, including all police contacts, arrests, court actions, and sentences. Self-reports can yield arrests and other criminal activities that do not appear on official records, arguably rendering them a more accurate reflection of an individual's true criminal past (19,20). However, the self-reporting method is not without its problems. For example, one problem involves the fact that most serious career criminals have offending careers that include potentially hundreds of arrests, convictions, and various punishments. Their criminal careers often span decades and involve many events precipitated or accompanied by drug and alcohol use. Thus, not only are there many criminal events, but career offenders may suffer from memory and other cognitive impairments stemming from an antisocial lifestyle. Therefore, self-reported criminal histories were supplemented with official records from the Interstate Identification Index (III) system. Under the III system, the FBI maintains an automated criminal record containing an FBI number and state identification number for each state holding criminal history information on an individual. The III records are accessed using the National Crime Information Center (NCIC) telecommunications lines that retrieve criminal records from repositories. Increasingly, researchers studying criminal careers are using both official and self-reported measures of criminal offending to assess and enhance validity of offender self-report data (21–23). In addition, this technique reduces missing data, increases reliability, and minimizes deficiencies of self-reported and official data collection strategies. Farrington et al. (24, p. 953) concluded, "there was a significant overlap between chronic offenders identified in court referrals and chronic offenders identified in self-reports. Therefore, to a considerable extent, self-reports and court referrals identified the same people as the worst offenders."

TABLE 1—*Characteristics of burglary offenders (n = 456).*

	n (%)	Mean (± SD)
Age		38.50 (10.66)
Gender		
Male	424 (93.0)	
Female	32 (7.0)	
Ethnicity		
White	256 (56.1)	
Hispanic	125 (27.4)	
African-American	49 (10.8)	
Native American	23 (5.0)	
Asian-American	3 (0.7)	
Offense onset		18.41 (4.99)
Burglaries		4.77 (4.89)
Criminal career		20.09 (10.01)
Total offenses		55.52 (32.61)

Data Analysis

Variants of finite mixture modeling such as latent class analysis (LCA) and LPA have become increasingly popular methods because of their ability to identify underlying patterns in data based on unobserved quantities (25). LCA uses categorical variables while LPA is employed with continuous variable measures. Latent variable modeling possesses numerous advantages not found in the related techniques of *k*-means or hierarchical cluster analysis. In LCA, results are model-based rather than based on *ad hoc* distance measures and as such employ maximum likelihood estimation procedures. In addition, covariates can be entered simultaneously with indicator variables without the additional computational steps necessary with traditional cluster analytic procedures. Similar to cluster analysis, however, final class solutions depend entirely on variables that are originally entered into the analysis.

As continuous variables were used to form latent subgroups, LPA was used to quantify the underlying patterns of homogeneity among burglars. The underlying assumption of LPA is that the relationship among continuous indicators can be explained by a categorical latent variable. The continuous indicators are considered to be locally independent, meaning that the observed items are statistically independent within each latent subgroup or class (26,27). Models were run using Latent GOLD® 4.0 software (Statistical Innovation, Belmont, MA) (28) with the goal of analyzing one to five classes. We could have included more classes, but maintaining parsimony is critical. Final optimal class solutions were based on several fit indices including maximum likelihood estimation using the Bayesian Information Criterion (BIC) where lower BIC values indicate model improvement. Additional fit indices, such as class error, number of parameters, and entropy were also examined.

Class assignment probabilities were also evaluated to assess class homogeneity. Conceptual fit of models is critical and was examined by using visual representations of the offense indicators to assess their interpretability and practical implications. Final class solutions should be theoretically interpretable and not merely reflect statistical fit optimization. Bivariate residuals were examined to ensure that the assumption of local independence was not violated; no violations were detected. ANOVA and chi-squared tests were used to compare mean differences and proportionality between external covariates. This technique not only enhances the validation of class solutions, but also provides important descriptive detail necessary to characterize subgroups of burglars. Finally, statistically significant variables derived from ANOVA were used in a multinomial logistic regression to assess simultaneous association in predicting subgroup membership.

Results

Latent Profile Analysis

We used 15 indicator variables that reflected a varied range of offense characteristics that prior typologies have suggested to be important, such as sex offenses, drug use, and span of criminal career. A total of five LPA models were examined, ranging from one to five classes. Each model was estimated with 50 random starts and 50 iterations, and no problems with local maxima were found. The empirical fit of the models and their estimated class sizes are summarized in Table 2. The one-class solution exhibited a poor fit with the data relative to the other models. The entropy values for all the models were very similar and greater than 0.90, indicating that offense and related characteristics employed were good predictors of class membership. Overall, the four-class solution exhibited the best empirical fit with the data based on the BIC.

The conceptual fit of the models was examined through visual inspection. This involved plotting the estimated mean values for each offense characteristic by each class (see Fig. 1). Class 1 was the largest subgroup identified (n = 264, 57.7%). This subgroup, labeled *young versatile*, did not have the criminal career span of the other subgroups and did not possess a unique characteristic offense pattern. Class 2, labeled *vagrants,* were the next largest subgroup (n = 98, 21.4%); such persons evidenced a distinctly high number of vagrancy offenses. Class 3 (n = 66, 14.8%) burglars were distinguished by a high number of aliases, drug possession offenses, and tattoos and were labeled *drug-oriented* burglars. Subgroup 3 also had the highest level of total offenses (M = 92.19). The final subgroup identified, Class 4 (n = 28, 6.1%) were

TABLE 2—*Fit indices for latent classes defined by offense and related characteristics.*

No. of Classes	LL	BIC (LL)	Npar	Class Error	Entropy
1	−19111.61	38713.01	80	0.0000	N/A
2	−16848.97	34683.66	161	0.0076	0.9707
3	−16262.17	34005.98	242	0.0098	0.9659
4	**−15861.62**	**33700.80**	**323**	**0.0330**	**0.9317**
5	−15676.41	33826.31	404	0.0221	0.9529

LL, log likelihood; BIC, Bayesian Information Criterion; Npar, number of parameters. Values in bold indicate the best model fit.

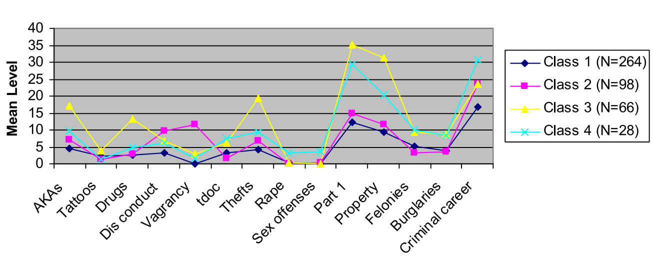

FIG. 1—*Profiles of burglar latent classes.*

characterized by a lengthy criminal career span (>30 years), sexual offenses including rape convictions and were labeled *sexual predator* burglars. Classes 3 and 4, the drug-oriented and sexual predator burglars had significantly more burglar offenses (M = 8.7 and 8.5, respectively) than subgroups 1 and 2. Given that the sample comprised of career offenders, all subgroups displayed offense versatility, yet as described above, there was also evidence of specialization particularly with respect to drug crimes and sexual offending.

Comparative Analysis

A comparative analysis of the four-class solution was conducted by examining the proportional and mean differences between burglary classes across demographic and offense characteristics (see Table 3). Chi-squared tests revealed class composition differences by gender (χ^2 [3] = 8.29, p = 0.04), ethnicity (χ^2 [2] = 40.17, p < 0.001), and age (F [3] = 25.49, p < 0.001). Class 3, drug-oriented burglars, had the highest percentage of females (7.6%), whereas Class 4, sexual predator burglars, comprised entirely of males. Class 1 was the youngest subgroup of burglars (M = 35.26, SD = 10.31) and Class 4 was the oldest (M = 47.43, SD = 11.36). Notably, Class 4 also had the earliest age of onset for offending (M = 16.96, SD = 3.57).

In terms of offense characteristics, Class 1, although versatile, did not stand out in any one category. Drug-oriented burglars (Class 3) were notable for drug-trafficking offenses (M = 16.96, SD = 3.57), motor vehicle theft (M = 16.96, SD = 3.57), forgery (M = 16.96, SD = 3.57), fraud (M = 16.96, SD = 3.57), and weapons offenses (M = 16.96, SD = 3.57). Class 4 (sexual predator burglars) was notable for solicitation of prostitution offenses (M = 16.96, SD = 3.57), robbery (M = 16.96, SD = 3.57), and aggravated assault (M = 16.96, SD = 3.57). Findings associated with external covariates validate the LPA for these subgroups. Validation of vagrant burglars (Class 2) was less clear and distinct compared with the other classes. Because of a low base rate and limited variability, no significant differences were found between classes with respect to murder.

To further explore differences between classes, a multinomial logistic regression model (overall model χ^2 = 67.67, p < 0.0001) was used with variables (arrest onset, history or number of motor vehicle theft, fraud, and weapons offenses) that ANOVA *post hoc* analyses identified as significant mean differences between classes. Class 1 served as the reference subgroup. As revealed in Table 4, relative risk ratios for membership in Class 2 (vagrant burglars) showed that age of onset (z = 2.43, p = 0.015) and weapons offenses (z = 3.54, p < 0.001) were important predictors. Age of onset of arrest was not a significant factor for predicting membership in Classes 3 and 4. However, for drug-oriented burglars, motor vehicle theft (z = 3.19, p = 0.001), fraud (z = 3.09, p = 0.002), and weapons offenses (z = 3.39, p = 0.001) heightened the risk for class membership. For sexual predators, weapons offenses (z = 2.25, p = 0.024) and fraud (z = 2.44, p = 0.015) were significant.

Discussion

This study employed a rigorous quantitative approach to develop a typology of burglars based on a sample of 456 adult career offenders. Findings revealed evidence of four relatively discrete subgroups of burglars: *young versatile, vagrants, drug-oriented*, and *sexual predators*. Young versatile burglars were characterized by relatively youthful age and a variety of offense types. These burglars may well escalate into additional specialty niches, but have

TABLE 3—*Chi-squared and ANOVA tests of external covariates across four classes of burglars (n = 456).*

	Class 1 (Young Versatile, n = 264), n (%)	Class 2 (Vagrants, n = 98), n (%)	Class 3 (Drug-Oriented, n = 66), n (%)	Class 4 (Sexual Predators, n = 28), n (%)	χ^2	p-Value
Gender						
Female	25 (4.5)	2 (2.0)	5 (7.6)	0 (0.0)	8.29	0.04
Male	239 (95.5)	96 (98.0)	61 (92.4)	28 (100.0)		
Ethnicity						
White	148 (56.1)	68 (69.4)	23 (34.8)	17 (60.7)	40.17	<0.001
Hispanic	82 (31.1)	17 (17.3)	22 (33.3)	4 (14.3)		
African-American	23 (8.7)	5 (5.1)	15 (22.7)	6 (21.4)		
Native American	8 (3.0)	8 (8.2)	6 (9.1)	1 (3.6)		
Asian-American	3 (1.1)	0 (0.0)	0 (0.0)	0 (0.0)		
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	F-statistic[*,†,‡,§,¶,**]	p-Value
Age	35.26 (10.31)	43.16 (9.09)	40.74 (8.62)	47.43 (11.36)	25.40[*,‡,§,¶]	<0.001
Onset	18.37 (5.20)	19.72 (5.10)	17.24 (4.03)	16.96 (3.57)	4.35[†]	0.005
Aggravated assault	1.70 (2.18)	2.39 (2.72)	2.36 (3.48)	3.36 (3.54)	4.73	0.003
Murder	0.13 (0.42)	0.08 (0.31)	0.09 (0.34)	0.18 (0.48)	0.619	ns
Robbery	0.60 (1.38)	0.65 (1.47)	1.38 (2.71)	1.82 (3.15)	6.59	<0.001
Weapons offenses	0.64 (1.18)	1.31 (2.74)	1.52 (2.24)	1.32 (2.41)	6.07[‡]	<0.001
Motor vehicle theft	1.28 (2.10)	1.11 (1.61)	3.14 (4.84)	2.32 (2.68)	10.59[†,‡]	<0.001
Drug sales/trafficking	0.45 (1.42)	0.59 (1.34)	1.80 (4.39)	0.71 (2.07)	7.09	<0.001
Prostitution	0.05 (0.46)	0.11 (1.11)	0.15 (1.01)	2.82 (12.56)	6.65	<0.001
Forgery	0.70 (1.91)	0.51 (2.13)	1.73 (4.51)	1.54 (2.67)	4.19	0.006
Fraud	1.41 (1.97)	1.10 (2.27)	3.15 (4.68)	2.79 (6.55)	8.40[†,‡]	<0.001

ns, not significant.
Bonferroni and Dunnett's T3 *post hoc* comparisons conducted for all ANOVAs.
*Classes 1 and 2 are different.
†Classes 2 and 3 are different.
‡Classes 1 and 3 are different.
§Classes 1 and 4 are different.
¶Classes 2 and 4 are different.
**Classes 3 and 4 are different.

TABLE 4—*Multinomial logistic regression results predicting membership in burglary subgroups (n = 456).*

	RRR	SE	z	p-Value	95% CI
Subgroup 2 (Vagrant burglars)					
Onset	1.059	0.025	2.43	0.015	1.011–1.109
Motor vehicle theft	0.974	0.063	−0.40	0.687	0.857–1.106
Fraud	0.927	0.060	−1.16	0.248	0.816–1.053
Weapons	1.302	0.097	3.54	<0.001	1.125–1.507
Subgroup 3 (Drug-oriented burglars)					
Onset	0.988	0.034	−0.33	0.740	0.923–1.058
Motor vehicle theft	1.177	0.060	3.19	0.001	1.065–1.302
Fraud	1.155	0.054	3.09	0.002	1.054–1.267
Weapons	1.306	0.103	3.39	0.001	1.119–1.524
Subgroup 4 (Sexual predator burglars)					
Onset	0.953	0.049	−0.92	0.357	0.861–1.055
Motor vehicle theft	1.106	0.077	1.45	0.148	0.964–1.268
Fraud	1.145	0.063	2.44	0.015	1.026–1.276
Weapons	1.261	0.130	2.25	0.024	1.030–1.544

RRR, relative risk ratios; CI, confidence interval.
Overall model, $\chi^2 = 67.67$, $p < 0.0001$.
Reference group = subgroup 1 (young versatile).

yet to be defined by any particular pattern. Vagrant burglars garnered numerous charges related to their transient status and appeared to burglarize for material gain and maintaining survival during winter months. Although the present investigation is hampered by a lack of clinical mental health and life circumstance variables, it may be that vagrant burglars are afflicted with mental health disorders and lack skills for gainful legal employment.

The final two classes—drug-oriented and sexual predator burglars—were more sharply defined and reflect descriptions of burglars based on qualitative research previously described. Drug-oriented burglars have had numerous drug possession and drug-trafficking offenses as well as high levels of theft and weapons offenses. They were also much more likely than the other subgroups to use aliases, social security numbers, and have tattoos. These findings paint a coherent picture of the drug-oriented burglar as pursuing illegal means of economic gain to satisfy their need for money to purchase illicit drugs. The high rate of weapons offenses is probably necessary because of the potential dangers inherent in drug use/marketing enterprises.

The final subgroup, sexual predator burglars, was clearly involved in high levels of sexual deviant acts such as rape and prostitution/solicitation offenses. There is also evidence that sexual predator burglars were the most violent. This subgroup possessed numerous aggravated assault and robbery charges. They also had the longest criminal careers—spanning over 30 years—and the earliest age of offense onset. Perhaps, the burglaries committed by this subgroup are at least partly motivated by sexual compulsions and thrills associated with entering the dwelling of a victim. Many burglaries may have been motivated by a strong desire for rape of a target that they had been stalking. This final subgroup may be the most dangerous of all with a high level of criminal persistence, intensity, and interpersonal violence. Two additional points are noteworthy about the sexual predator burglars. First, Class 4 comprised 6.1% of all offenders but was disproportionately involved in the most serious forms and total incidence of crime. Empirically, the 6.1% prevalence estimate is similar to the 5% threshold used to define career criminality (18,29,30). Second, recent analyses of a sample of 654 murderers found that offenders with prior arrests and convictions for rape and current involvement in burglary were significantly more likely to commit multiple homicides (31). In this way, the offense mix exhibited by the sexual predators is potentially a precursor for even more serious homicide offending and an important avenue for future research.

In addition to these empirical linkages to criminal careers research, the current study also bears on important theoretical issues. Early offender typologies soon fell out of favor because they were empirically weak and often not mutually exclusive (5,6,18,29). The typology issue relates to a large theoretical question centering on the validity of general theories that explain criminal careers from an underlying propensity perspective (32) and developmental theories that explain criminal careers as they relate to life circumstances and involvement in social institutions (33,34). Unfortunately, because the current study lacked data on employment, education, and marital status, we were unable to assess how and whether the offending behavior of the four classes changed according to life circumstances. For instance, McGloin et al. (35) found that criminal careers are best understood when short-term institutional relationships are known. In their study, offenders who were unmarried tended to be more versatile in their offending patterns whereas married offenders had constrained opportunities to offend and were more specialized. Developmental theories and research thus provide context to criminal careers and illuminate ways that getting married, having a job, and going to school decrease antisocial behaviors. The lack of data on life circumstances and the informal social controls rendered by marriage, job, and school is an important limitation of the current study.

It is also important to note that the LPA of the four burglary groups is specific to the current data and that replications with other datasets could probably produce different estimates and groupings. In no way should current burglary classes be reified. Interestingly, quantitatively sophisticated analytical techniques are producing typologies of offenders that in some ways are reminiscent of early, qualitative efforts. For instance, semi-parametric group-based and LCAs allow for the study of criminal careers data to compare discrete groups of offenders who are homogeneous within their grouping or trajectory but different from other groupings or trajectories. Based on the shape of the offending trajectories over time, scholars are identifying "groups" of offenders with an assortment of labels, such as nonoffenders, adolescence-peaked, low-rate-, high-rate-, and late-onset chronics; classic desisters, moderate-rate desisters, low-, moderate-, and high-rate chronics. Yet even today, there appears to be dissatisfaction with the substantive worth of these approaches. For example, Eggleston et al. (36) concluded that "there is always a danger when a particular methodology approaches hegemonic status within a field of inquiry. At such a point questions are no longer asked and researchers unthinkingly apply the method of the day." Despite advances in data analysis techniques, the easy compartmentalization of offender groups that typologies promise has yet to be realized. Although *young versatile*, *vagrant*, *drug-oriented*, and *sexual predators* were the four groups to emerge from the current analyses, it should be noted that these groups generally had extensive criminal careers characterized by involvement in diverse forms of offending. Even significant evidence for categorization must be tempered with additional evidence of versatility that would seem to challenge categorization.

Although this investigation is one of the largest studies of burglary typologies to date, a larger sample would have provided greater statistical power to detect small to moderate effect size differences between subgroups. Future studies should attempt to include some of the aforementioned variables and perhaps, personality inventories as well. Combined quantitative and qualitative approaches in a single study would be able to further illuminate and refine future typologies. Further, little is known about the interactional dynamics of burglars in terms of their decision-making and opportunities (3) and therefore information on these processes would yield practical benefit. Given that burglary is a fairly prevalent crime causing extensive economic and mental harm to victims, larger and more intensive studies of the types of burglars that exist would provide much needed information for crime prevention services and aid forensic criminal investigation.

References

1. Federal Bureau of Investigation. Crime in the United States, 2006. Washington, DC: U.S. Department of Justice, 2007.
2. DeLisi M, Gatling JM. Who pays for a life of crime? An empirical assessment of the assorted victimization costs posed by career criminals. Crim Justice Stud 2003;16:283–93.
3. Hochstetler A. Opportunities and decisions: interactional dynamics in robbery and burglary groups. Criminol 2001;39:737–63.
4. Piquero A, Rengert GF. Studying deterrence with active residential burglars. Just Q 1999;16:451–71.
5. Blumstein A, Cohen J, Roth JA, Visher CA. Criminal careers and "career criminals." Washington, DC: National Academy Press, 1986.
6. Piquero AR, Farrington DP, Blumstein A The criminal career paradigm: background and recent developments. In: Tonry M, editor. Crime and justice: a review of research, Vol. 30. Chicago, IL: University of Chicago Press, 2003;359–506.
7. Bennett T, Wright R. Burglars on burglary. Aldershot, Kent, U.K.: Gower Publishing, 1984.
8. Cromwell P, Olson J, Avary D. Breaking and entering: an ethnographic analysis of burglary. Newbury Park, CA: Sage, 1991.
9. Decker S, Wright R, Redfern A, Smith D. A woman's place is the home: females and residential burglary. Just Q 1993;10:143–62.
10. Maguire M, Bennet T. Burglary in a dwelling: the offence, the offender and the victim. London, U.K.: Heinemann, 1982.
11. Shover N. The social organization of burglary. Soc Probl 1973;20:499–514.
12. Taylor M, Nee C. The role of cues in simulated residential burglary: a preliminary investigation. Br J Criminol 1988;28:396–401.
13. Wright R, Decker SH. Burglars on the job: street-life and residential break-ins. Boston, MA: Northeastern University Press, 1994.
14. Shover N. Burglary. In: Tonry M, editor. Crime and justice: a review of research, Vol. 14. Chicago, IL: University of Chicago Press, 1991;73–113.
15. Shover N. Great pretenders: pursuits and careers of persistent thieves. Boulder, CO: Westview, 1996.
16. Schlesinger L, Revitch E. Sexual burglaries and sexual homicides. J Am Acad Psychiatry Law 1999;27:228–39.
17. DeLisi M. Extreme career criminals. Am J Crim Justice 2001;25:239–52.
18. DeLisi M. Career criminals in society. Thousand Oaks, CA: Sage, 2005.
19. Dunford FW, Elliott DS. Identifying career offenders using self-report data. J Res Crime Delin 1984;21:57–86.
20. Elliott DS, Huizinga D, Morse B. Self-reported violent offending: a descriptive analysis of juvenile violent offenders and their offending careers. J Interpers Violence 1986;1:472–514.
21. Brame R, Fagan J, Piquero AR, Schubert CA, Steinberg L. Criminal careers of serious delinquents in two cities. Youth Violence Juv Just 2004;2:256–72.
22. Eggleston EP, Laub JH. The onset of adult offending: a neglected dimension of the criminal career. J Crim Justice 2002;30:603–22.
23. Geerken MR. Rap sheets in criminological research: considerations and caveats. J Quant Criminol 1994;10:3–21.
24. Farrington DP, Jolliffe D, Hawkins JD, Catalano RF, Hill KG, Kosterman R. Comparing delinquency careers in court records and self-reports. Criminol 2003;43:933–58.
25. Lanza ST, Flaherty BP, Collins LM Latent class and latent transition analysis. In: Schinka JA, Velicer WF, editors. Handbook of psychology: research methods in psychology, Vol. 2. Hoboken, NJ: John Wiley and Sons, 2003;663–85.
26. Lazarsfeld P, Henry N. Latent structure analysis. Boston, MA: Houghton Mifflin, 1968.
27. Ruscio J, Ruscio AM. A nontechnical introduction to the taxometric method. Understanding Statistics 2004;3:151–93.
28. Vermunt JK, Magidson J. Latent Gold 4.0 user's guide. Boston, MA: Statistical Innovations, 2005.

29. Piquero AR, Farrington DP, Blumstein A. Key issues in criminal career research: new analyses of the Cambridge Study in Delinquent Development. New York: Cambridge University Press, 2007.
30. Wolfgang ME, Figlio RM, Sellin T. Delinquency in a birth cohort. Chicago, IL: University of Chicago Press, 1972.
31. DeLisi M, Scherer AM. Multiple homicide offenders: offense characteristics, social correlates, and criminal careers. Crim Justice Behav 2006;33:367–91.
32. Gottfredson MR, Hirschi T. A general theory of crime. Stanford, CA: Stanford University Press, 1990.
33. Sampson RJ, Laub JH. Crime in the making: pathways and turning points through life. Cambridge, MA: Harvard University Press, 1993.
34. Laub JH, Sampson RJ. Shared beginnings, divergent lives: delinquent boys to age 70. Cambridge, MA: Harvard University Press, 2003.
35. McGloin JM, Sullivan CJ, Pratt TC, Piquero AR. Local life circumstances and offending specialization/versatility: comparing opportunity and propensity models. J Res Crime Delinq 2007;44:321–46.
36. Eggleston EP, Laub JH, Sampson RJ. Methodological sensitivities to latent class analysis of long-term criminal trajectories. J Quant Criminol 2004;20:1–26.

Additional information and reprint requests:
Matt DeLisi, Ph.D.
Iowa State University
203A East Hall
Ames, IA 50011-1070
E-mail: delisi@iastate.edu